IMAGE UNDERSTANDING USING OVERLAYS

Final Report
to
U. S. Army Night Vision and Electro-Optics Laboratory
Fort Belvoir, VA 22060

under
Contract DAAG53-76C-0138
(DARPA Order 3206)

Prepared by
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Computer Science Center
University of Maryland
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1. Introduction

This project is concerned with the study of advanced techniques for the analysis of reconnaissance imagery. It is being conducted under Contract DAAG-53-76C-0138 (DARPA Order 3206), monitored by the U.S. Army Night Vision Laboratory, Ft. Belvoir, VA (Dr. George Jones). The Westinghouse Systems Development Division, as a subcontractor, is investigating implementation of the techniques being developed by Maryland; the subcontract is entitled "Architecture for higher level digital image processing". Dr. Glenn E. Tisdale is program manager for Westinghouse, and Dr. Azriel Rosenfeld is principal investigator at the University of Maryland.

The current phase of this project, initiated in April 1978, is a continuation of a project entitled "Algorithms and Hardware Technology for Image Recognition" (May 1976-March 1978). The earlier project [1] was concerned primarily with tactical target detection on forward-looking infrared (FLIR) imagery. Specific efforts involved image modeling, smoothing, noise cleaning, edge detection and thinning, thresholding, tracking, feature extraction, and classification. Through the use of convergent evidence, based on coincidences between edge maxima and borders of above-threshold regions, excellent object extrac tion performance was achieved. Westinghouse studied the CCD implementations of many of the algorithms that were developed,

and breadboarded one basic function, a sorter. Communication among the Maryland, Westinghouse, and NVL groups was very good and lead to greatly accelerated transfer of advanced image understanding techniques.

The current project is concerned with the development and application of advanced techniques for image processing, feature detection, segmentation, texture and shape analysis, and region representation. (The "overlays" in the project title refer to region representations which specify background areas or possible object locations.)

Section 2 of this report summarizes accomplishments on the project during the past six-month period. Summaries for earlier periods can be found in previous Semiannual Reports [2-4]; these reports also appear as Project Status Reports in the semiannual DARPA Image Understanding Workshops [5-8].

The project is expected to continue for an additional two-year period, under the title "Understanding Features, Objects, and Backgrounds". Section 3 summarizes the proposed efforts to be conducted during this period.

Section 4 lists the individual reports issued and papers published during the current phase of the project, arranged by type and subject. The contents of the Quarterly Reports on the Westinghouse subcontract [9-15] are summarized in the Appendix.

2. Semiannual Report for the period 1 October 1979-30 March 1980

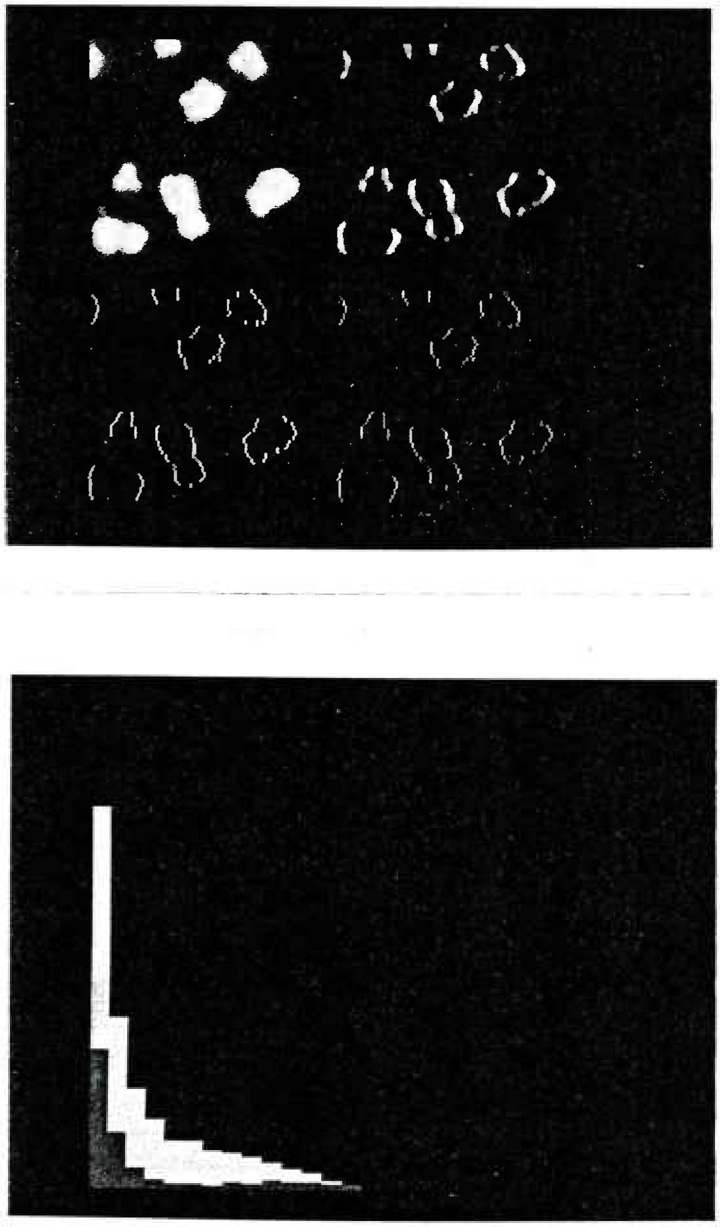
In this section, activities on the project during the past six months are reviewed under three headings: (1) segmentation and texture analysis; (2) local and global shape analysis; (3) hierarchical representation. Numbers in brackets refer to the technical reports listed in Section 4.

2.1 Segmentation and texture analysis

A. Edge detection

Edges are generally detected by thresholding the output of some type of difference operator; but the choice of a threshold for this purpose is not easy, since the histogram of difference values tends to fall off smoothly from a peak near zero. Threshold selection becomes easier if we suppress non-maximum difference values (in the gradient direction) before histogramming. As Figure 1 shows, this yields a histogram composed of a sharpened peak near zero together with small sets of higher values; the latter are likely to be good choices for edge points [67].

Difference operators for edge detection can be designed by fitting a polynomial surface to the gray levels in the neighborhood of a point, and taking the gradient of that surface as an estimate of the image gradient. This approach can be generalized to the design of operators for surface detection in three- (or higher-) dimensional arrays of data, such as



a b

d c

e

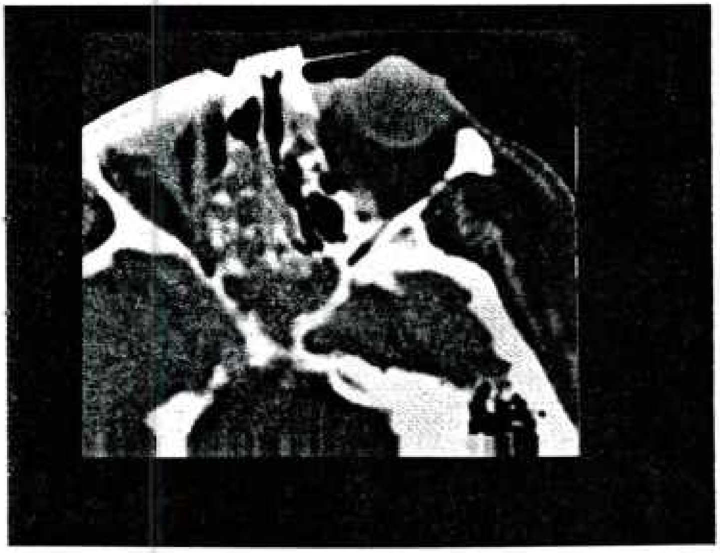
Figure 1. Nonmaximum suppression as an aid in edge detection. (a) Image; (b) digital (Sobel) gradient magnitudes; (c) results of suppressing nonmaxima in the gradient direction; (d) results of thresholding (b) at 6; (e) histograms of (b) and (c) superimposed.

those obtained by reconstructing objects from x-ray projections, by stacking cross-sections, or by stacking successive frames in a time sequence of images. Surface detection provides results that are more accurate and more reliable than those obtained by applying two-dimensional edge detectors to the individual slices, as can be seen from Figure 2. This work is part of a Ph.D. thesis on processing and segmentation of three-dimensional arrays.

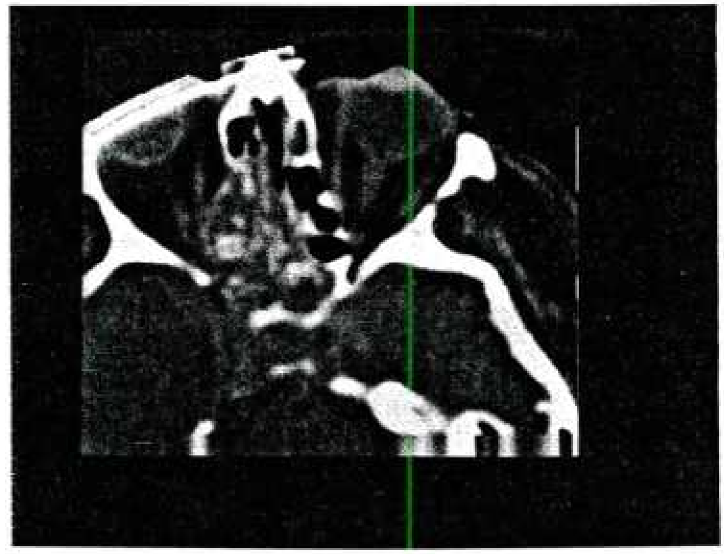
B. Pixel classification and texture analysis

During the past reporting period, an M.S. thesis was completed [55] on a general-purpose software package for performing relaxation operations on arrays of pixels. This package allows the user to specify the process for computing initial probabilities, the neighborhood to be used, and the probability adjustment algorithm (including the compatibility coefficients). As an application, a light/dark relaxation process was implemented; examples of this process can be found in earlier status reports [3,6]. Some analytical results regarding such two-label relaxation processes can be found in the sixth quarterly report on the Westinghouse subcontract [14].

Relaxation has been successfully used to improve pixel classification based on color, as reported elsewhere. It can similarly be used to improve pixel classification in single-band images based on local property values such as gray level and "busyness". Figure 3a shows a house picture containing



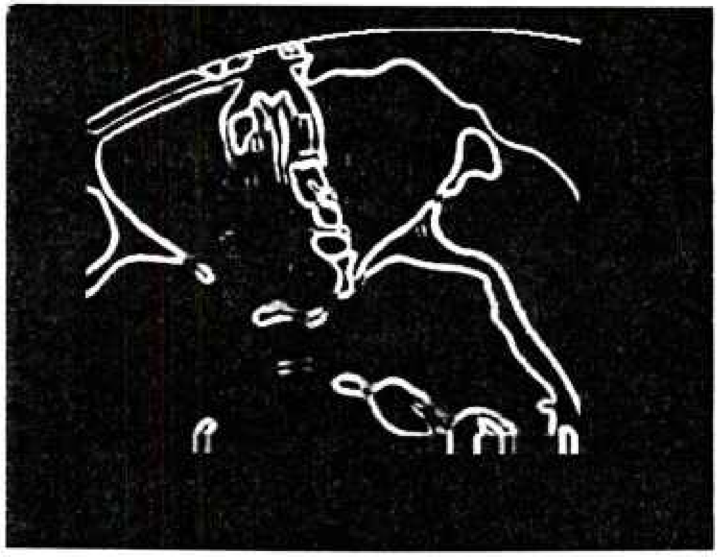
a



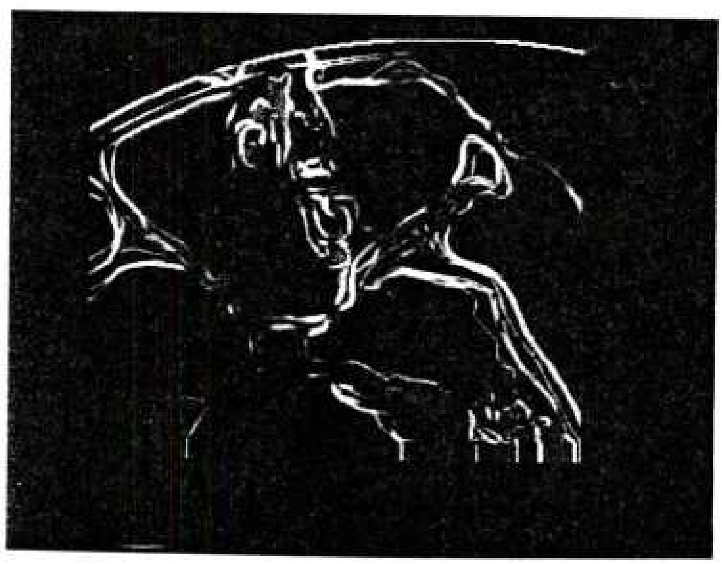
b

c

Figure 2 (see next page for caption)



d



e

Figure 2. Surface detection in 3-d arrays. (a-c) Three consecutive cross-sections of a CT reconstruction; (d) results of applying the 2-d Prewitt operator to the middle cross-section; (e) results of applying a 3-d Prewitt operator to the three cross-sections.

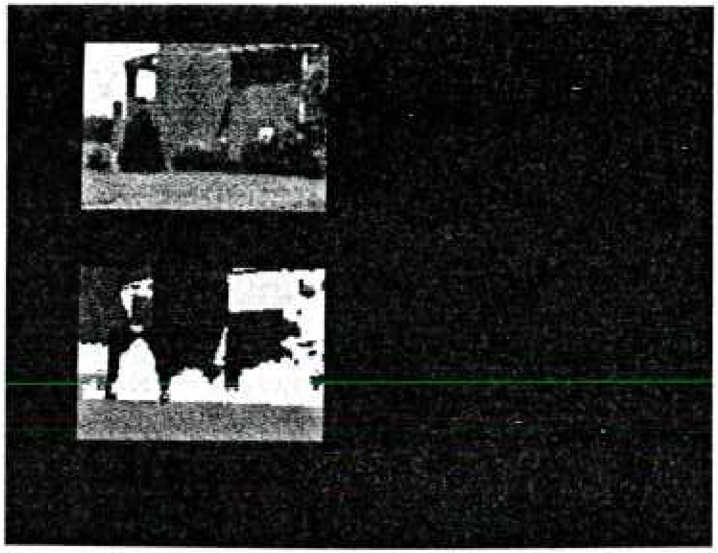
five principal types of regions--sky, grass, bushes, brick, and shadow. The bush and shadow classes are very difficult to distinguish; they have similar mean vectors, and the bush class is more variable, so that a maximum-likelihood classification (based on Gaussian fitting to the clusters defined by hand segmentation) misclassifies most of the shadow pixels as bush (Figure 3b). The results are greatly improved when relaxation is used to adjust the initial class probabilities for each pixel based on those of its neighbors; see Figure 3c. Similar improvement is obtained when the busyness values are iteratively smoothed, e.g. by median filtering, prior to clustering and classification (Figure 3d). Further details on these experiments can be found in [65].

Iterative smoothing can also be used to improve the results of texture classification using texture features derived from small windows, as described in [56].

C. <u>Iteractive segmentation</u>

An interactive image segmentation system is being designed as a contribution to the DARPA/DMA Testbed. The system allows the user to designate samples of two classes (e.g., objects and background). It analyzes the samples, designs a classifier to discriminate them, and displays the classification results to the user for evaluation; if errors are designated, the system attempts to modify the classifier so as to eliminate them. The user need not know anything about the classification

a



c

Iteration of relaxation	Fraction of class correctly classified 1	2	3	4	5
0	.925	.938	.874	.057	.876
1	.933	.920	.871	.063	.872
2	.933	.921	.875	.067	.875
3	.933	.921	.876	.072	.874
4	.935	.921	.878	.157	.871
5	.937	.921	.880	.330	.841
6	.937	.921	.881	.413	.824
7	.938	.921	.881	.465	.820
8	.938	.921	.881	.500	.815

b

Class	Fraction classified as 1	2	3	4	5
1	.925	.003	.023	.003	.047
2	.011	.938	.028	.002	.021
3	.114	.002	.874	.000	.011
4	.019	.006	.003	.057	.914
5	.085	.005	.008	.025	.876

d

Iteration of medium filtering	Fraction of class correctly classified 1	2	3	4	5
0	.925	.938	.874	.057	.876
1	.897	.937	.915	.535	.866
2	.900	.940	.921	.536	.866
3	.901	.939	.921	.534	.867
4	.903	.937	.922	.531	.872

Figure 3. Segmentation based on gray level and local "busyness". (a) Image (top) and hand segmentation (bottom). (b) Confusion matrix for maximum-likelihood classification of the pixels into sky, brick, grass, bush and shadow, based on bivariate Gaussian fitting to the populations obtained by hand segmentation; note that the shadow class is mostly classified as bush. (c) Results of applying probablistic relaxation to initial classifications based on Gaussian fitting; note the gradual improvement. (d) Results of smoothing the busyness values by median filtering prior to clustering and classification; the improvement is immediate.

process or the features that are used for classification; the system selects them from a prespecified repertoire. The current, pilot version of the system classifies pixels based on gray level only; future versions will make use of various types of local features and will allow more than two classes.

D. Mosaicking

A relaxation method for eliminating seams from photomosaics without degrading image detail is described in [72].

2.2 Local and global shape analysis

A. Corner detection

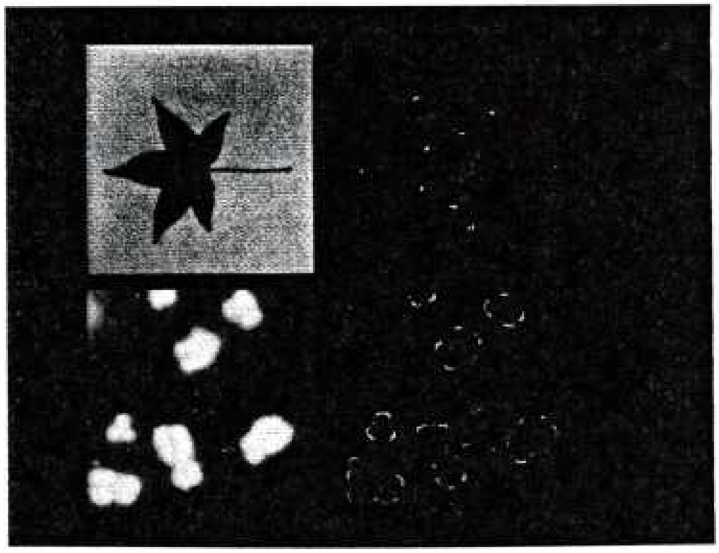
Several types of operators have been developed that respond to the presence of "corners" (i.e., sharp changes in edge direction) in an unsegmented image [69]. For example, one can express the rate of change in the gradient direction in terms of first and second derivative operators; or one can simply compute a digital gradient direction, and estimate its rate of change at P by comparing it with the directions at the appropriate neighbors of P. To measure "cornerity", the rate of change in gradient direction should be multiplied by the gradient magnitude, since we are only interested in corners that lie on edges. Figure 4 shows a display of cornerity values for a simple grayscale image; the results seem reasonable.

B. Collinearity and parallelism

Collinear and parallel (or "antiparallel") sets of edge and line segments are important elements in the description of many types of scenes. The following paragraphs describe general-purpose programs for analyzing collinearity and parallelism. A more specialized program that links edge segments based on gray level, as well as geometric, criteria, with application to the detection of buildings and roads on aerial imagery, will be described in a forthcoming report; see [85].

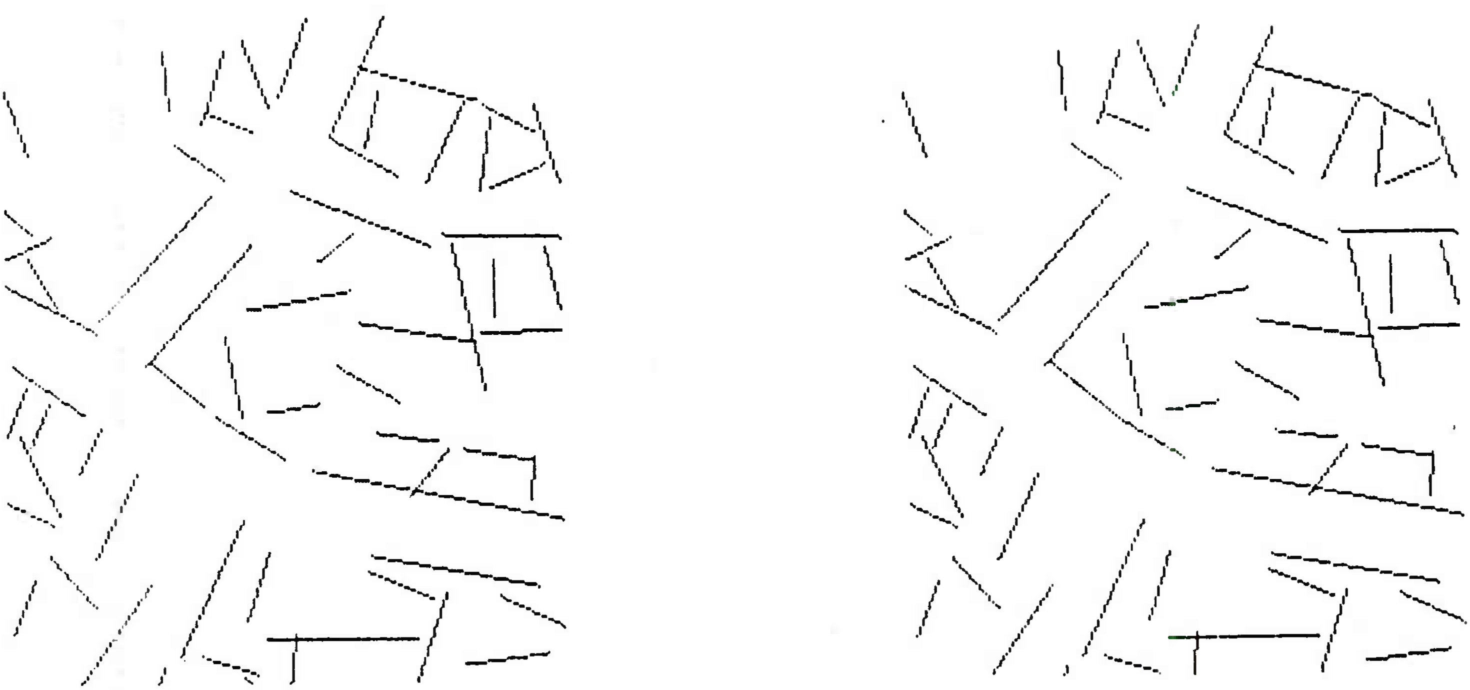
The "collinearity strength" of two segments depends on several factors:

a



b

Figure 4. Corner detection in grayscale images. (a) Image; (b) results of "cornerity" computation.



1.00 .80

Figure 5 (see next page for caption)

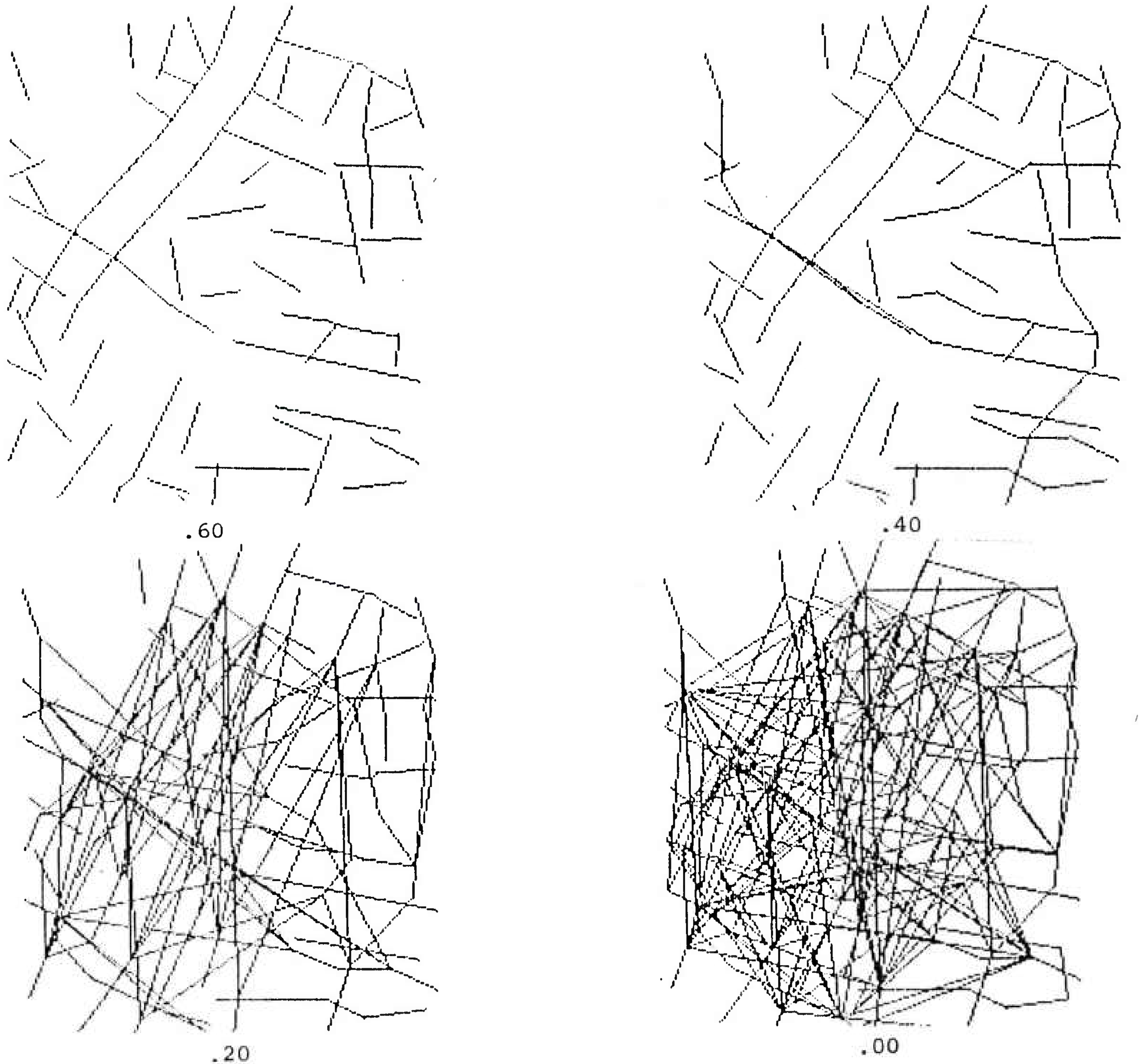


Figure 5. Collinearity linking: segment pairs whose collinearity merit is at least p, for p = 1, .8, .6, .4, .2, and 0.

(a) The distance between their nearer ends, relative to their lengths

(b) The angles that they make with the line joining their nearer ends

(c) The distance between their farther ends, relative to the nearer-end distance and lengths.

A collinearity strength measure based on a combination of these factors gives generally reasonable results, as illustrated in Figure 5 [67].

Collinear segments can be grouped into "clusters" based on their relative sizes and separations. Several types of cluster merit functions can be used for this purpose; a good figure of merit should depend on both the segment density and the total segment length in the given cluster. Examples of clusters defined by maximizing such a figure of merit are given in Figure 6. For a report on these experiments see [70].

Segments can also be linked based on parallelism (or, in the case of edge segments, antiparallelism: the dark sides of the edges should face in opposite directions). The figure of merit for this linking process should depend on the separation of the segments, their lengths and the amount by which they overlap, as well as their parallelism (i.e., the angle between them). Mutually best pairs based on this merit function can be linked, and the process can then be repeated with the linked pairs eliminated. For examples of the results obtained using this approach see [57].

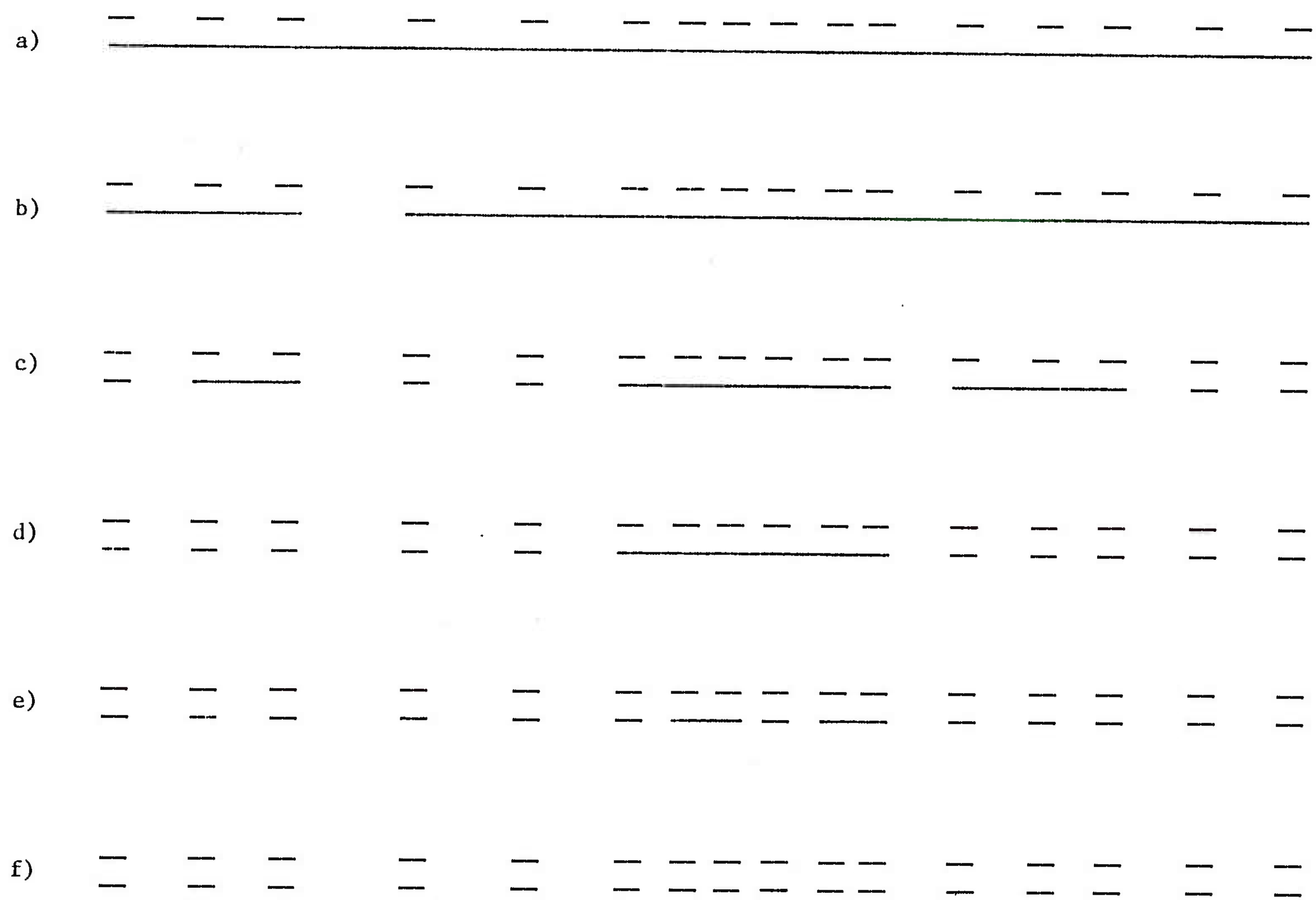


Figure 6. Collinear clusters of segments. The input is repeated on each line, with the results of clustering shown below it for successively higher values of a clustering parameter. For the value used in (d), the central cluster is linked together and no other segments are linked.

C. The medial axis

The medial axis (MA) of a set S is defined as the set of centers (and radii) of the maximal "disks" contained in S, or equivalently, as the set of points of S whose distances from the complement $\overline{S}$ are local maxima. It can be used as a compact representation of S, and can also serve as a basis for approximating S by a union of "generalized ribbons" (= connected arcs of MA points, with radii specified by a "width function" defined along each arc).

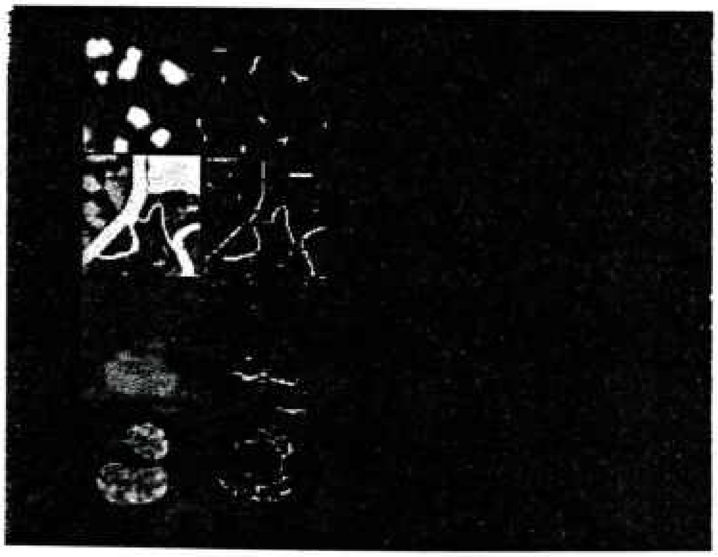
The MA is sensitive to noise, i.e., to errors in extracting the set S; thus it would be desirable to define it directly for unsegmented images. This can be done using a "gray-weighted" concept of distance, but it is hard to reconstruct the image from such an MA. Another possibility (the "SPAN": Spatial Piecewise Approximation by Neighborhoods) is to approximate the image by maximal homogeneous disks, but the approximation process is computationally costly. Still another alternative is to assign an MA score to each point P based on the presence of high gradient values at pairs of positions symmetrically located with respect to P; but this process turns out to be quite sensitive to noise.

A more robust approach to defining an MA for unsegmented images is based on a characterization of the MA of a set S in terms of shrinking and expanding operations performed on S. Let $S^{(-n)}$ denote the result of shrinking S (i.e., deleting its

border) n times, and similarly let $S^{(n)}$ denote the result of expanding S n times ($S^{(n)} = \overline{\overline{S}^{(-n)}}$). Then it is not hard to see that $S_k \equiv (S^{(-k)})^{(1)} - S^{(-k+1)}$ is the set of MA points at distance k from $\overline{S}$, so that $\cup S_k$ is the MA. To generalize this to unsegmented images, we use local MIN operations instead of shrinking, and local MAX operations instead of expanding; we can then define the "MMMAT" (= min-max MAT) as ΣS_k. Examples of such MMMATs are shown in Figure 7; for further details see [61]. Approximations to the image can be reconstructed by using only points having strong MMMAT values, and k's that make strong contributions to these values. For examples of such reconstructions see Figure 8; see [73] for a report on this work.

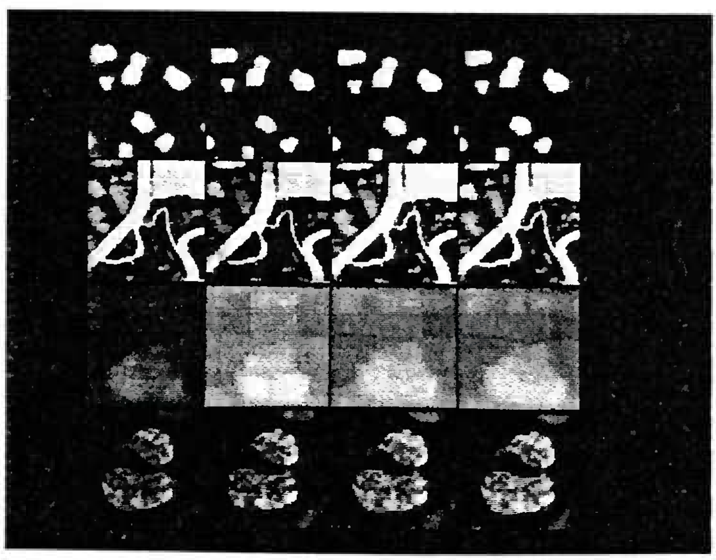
D. Shape segmentation

Various types of shape features, such as protrusions and intrusions, can be detected by comparing boundary arcs with their chords; for example, if the chord is much shorter than the arc, or if the arc does not lie close to the chord, that arc must be a proptrusion or intrusion. Suppose that we measure various arc-chord figures of merit (e.g., arc length divided by chord length, or area between arc and chord divided by squared chord length) for every arc. In many cases, extrema of such figures or merit correspond to arcs that are natural "pieces" of the shape, as illustrated in Figure 9. However,



(a) (b)

Figure 7. The min-max medial axis transformation (MMMAT). (a) Images; (b) MMMATs.



(a) (b) (c) (d)

Figure 8. Reconstruction from the MMMAT. (a) Original images; (b-d) reconstructions from the one, two, and three largest increments at those points having values above the 25th percentile (189, 582, 226, and 462 out of 4096 pixels, in the four cases).

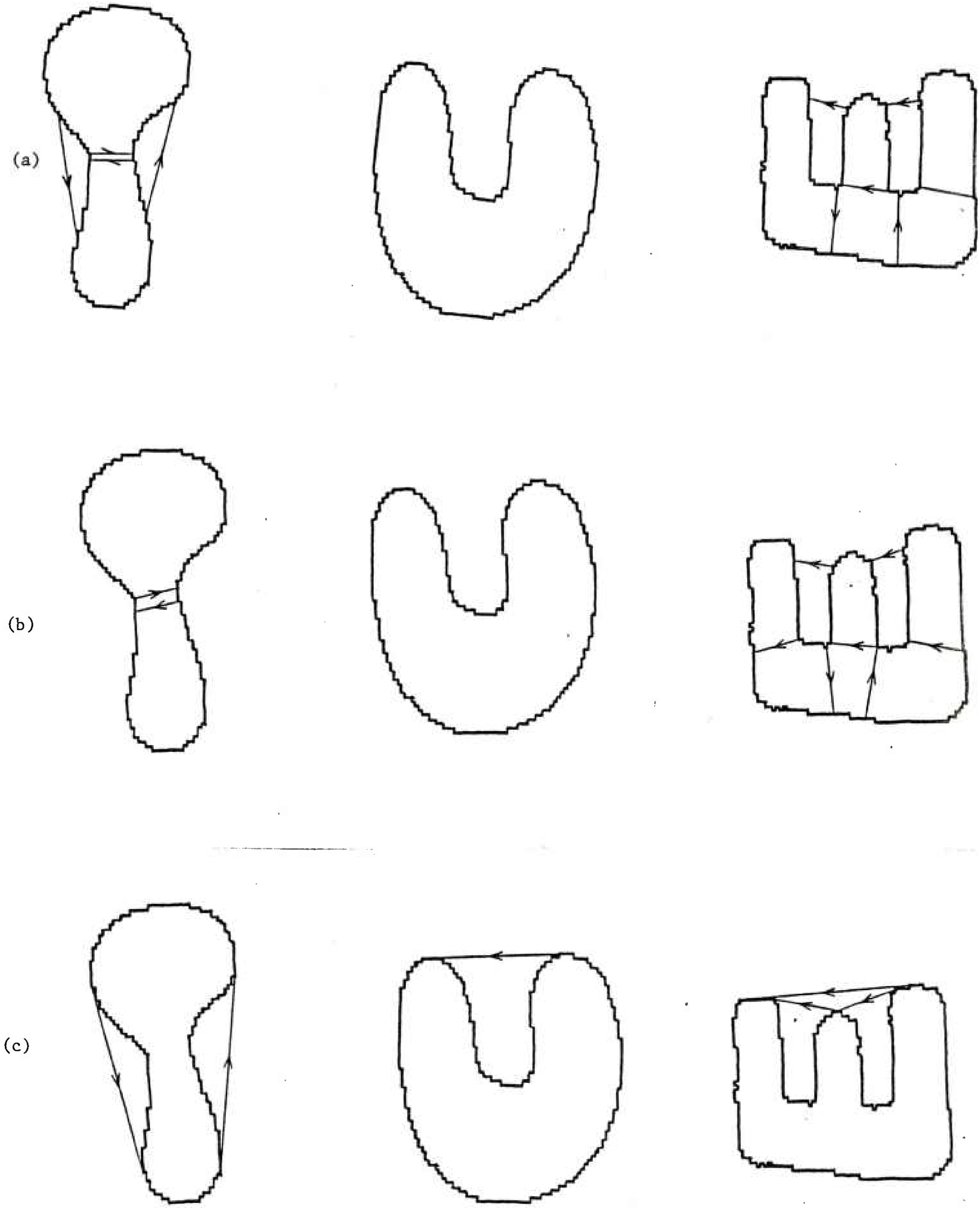


Figure 9. Shape segmentation based on extrema of arc/chord functions. (a) Maxima of area/chord^2; (b) maxima of arc/chord; (c) negative maxima of area.

this approach sometimes leads to segmentations that are not intuitively plausible, since the extreme depend only on (e.g.) the curve's slopes at the arc endpoints, and not on the shape of the arc between the endpoints; see [59].

Work on shape segmentation using relaxation, described in earlier reports, is being extended to handle shapes with major occlusions or missing parts; the results will be described in a forthcoming report.

2.3 Hierarchical representation

A. Quadtrees and hextrees

The quadtree algorithms developed on this project usually involve locating neighbors of a given block in the image by searching the tree starting from the corresponding node. A general treatment of neighbor finding in quadtrees, including an analysis of the expected computational costs, can be found in [62].

Quadtrees are defined on the basis of recursive subdivision into quadrants; they involve square blocks, and four blocks of a given size constitute a block of the next larger size. For some purposes it may be desirable to define a representation based on hexagonal rather than square blocks, since such a representation would be less sensitive to rotation. Hexagons cannot be combined to form exact hexagons of a larger size, but one can combine seven hexagons into a "ragged" hexagon, and this process can be iterated, as illustrated in Figure 10. A detailed discussion of how to define hexagonal "pyramids" in this way can be found in [54].

B. Quadtree shape approximation

When a region is represented by a quadtree, the upper levels of the tree, corresponding to large blocks of the image, define approximations to the region. These approximations can be used to estimate shape properties such as moments, and to speed up shape matching by eliminating gross mismatches

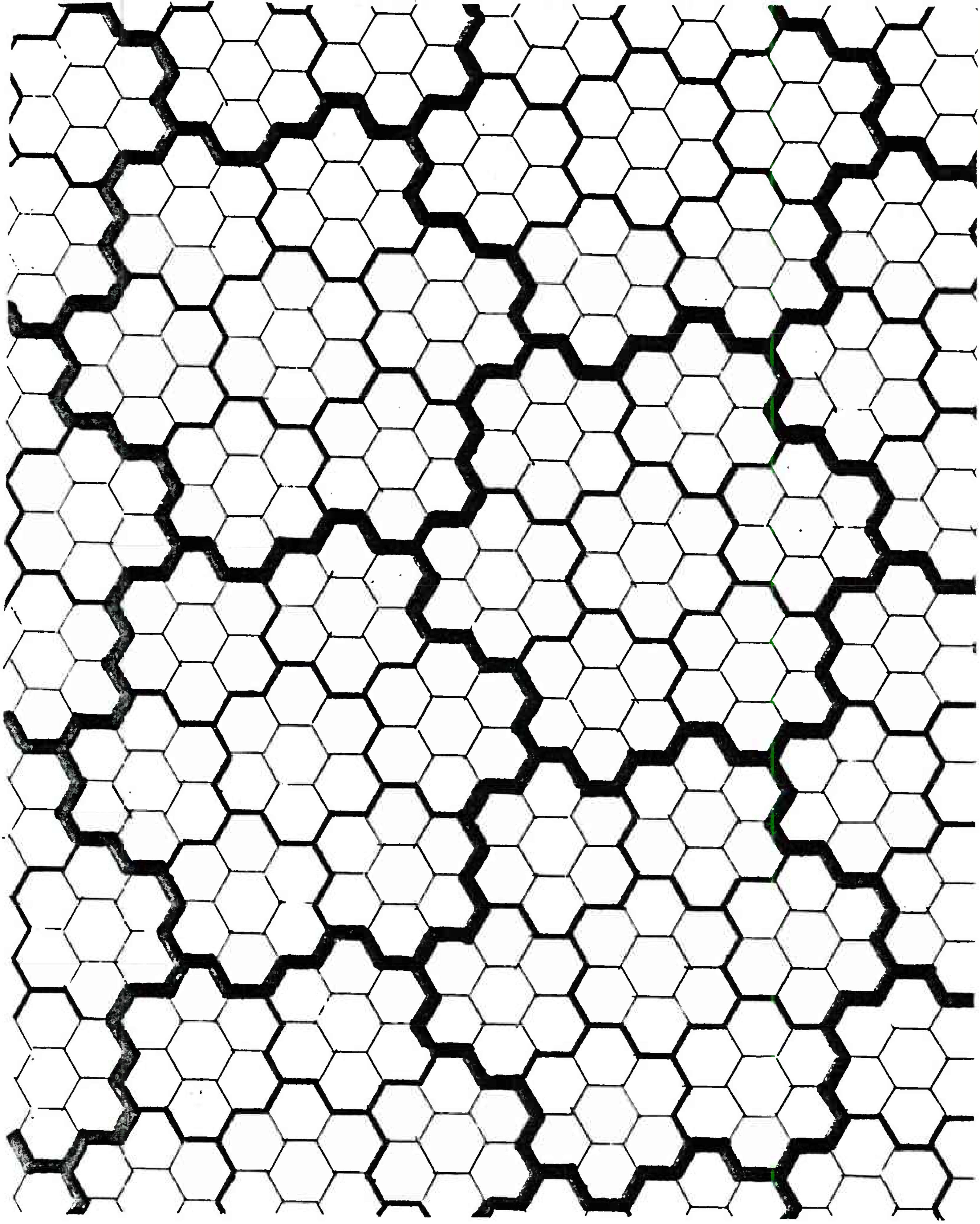


Figure 10. Hierarchical hexagonal grid (three levels).

rapidly [58]. For example, the coordinates of the centroid of a shape can be estimated to a fraction of a pixel using quadtree approximations, as illustrated in Figure 11. This should make it possible to track moving shapes quite accurately; even though the quadtree itself changes radically when a shape is shifted, the moment approximations remain stable. Similarly, the approximations can be used to determine upper and lower bounds on the mismatch area; thus if we are matching a given shape S_j against a collection of stored shapes $S_1, S_2, \ldots,$ we can eliminate any S_i such that the lower bound on the mismatch of S_j with S_i exceeds the upper bound on the mismatch of S_j with some other shape. This error bounding process is illustrated in Figure 12.

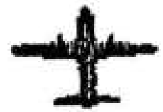
C. Hierarchical image processing and segmentation

Extensive work is now in progress on the use of pyramid structures for image processing and segmentation. The following are some of the chief areas of investigation:

a) Iterated local convolution operations can be used to produce large-kernel convolutions having almost exactly Gaussian kernels. These can in turn be combined to yield various types of circular or elongated center-surround operators [63].

b) Image pyramids can be defined in which the blocks at each level overlap; this largely negates the objections to conventional power-of-2 pyramids on grounds of shift sensitivity.

(a)

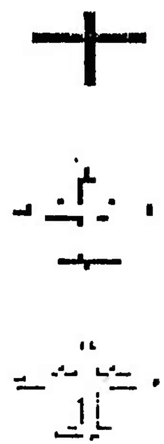


(b): Level

2

1

0



(c) Level	No. of nodes	Area	Centroid coordinates
2	15	240	35.63,33.50
1	53	392	34.64,32.38
0	155	494	34.17,32.36

Figure 11. Approximating the centroid of a shape using its quadtree representation. (a) Airplane. (b) Black nodes at each level of the quadtree representation of (a), displayed as black blocks. (c) Cumulative number of nodes, area, and centroid coordinates as a function of level.

(a) (b)

a to a

L	LB	UB
1	0	4096
2	0	2048
3	0	1152
4	0	608
5	0	212
6	0	0

b to b

L	LB	UB
1	0	4096
2	0	2304
3	0	1216
4	0	592
5	0	200
6	0	0

a to b

L	LB	UB
1	0	4096
2	0	2816
3	0	1600
4	352	1392
5	504	900
6	601	601

(c)

Figure 12. Lower and upper bounds on the mismatch when two airplanes are matched to themselves and to each other (L=level, LB=lower bound, UB=upper bound). Note that at level 5, the lower bound on the mismatch to each other exceeds the upper bounds on the mismatches to themselves.

c) In an overlapped pyramid, by associating nodes with their most similar ancestors, one can establish linked clusters of nodes representing homogeneous regions; this facilitates smoothing or segmentation of the regions.

d) Local operations in a pyramid can be used to detect simple types of objects in the image, and to extract these objects by local thresholding. This approach was applied to blob-like objects in an earlier report; it has now been extended to streak-like objects [60].

e) Pyramids can be used to define quadtree approximations to an image ("Q-images), based on the concept that a block is subdivided only if it is unhomogeneous.

f) The use of Q-images facilitates segmentation by thresholding, since the peaks in the histogram of a Q-image (where each block contributes its mean gray level, a number of times proportional to its size) tend to be sharper and more cleanly separated. The histogram is further improved when we eliminate small blocks, since these tend to lie on region borders. Conversly, if we histogram only the small blocks, we obtain a unimodal histogram whose mean is a good threshold [68]. More generally, we can find blocks in the quadtree corresponding to peaks in the histogram, and

apply local thresholds in the vicinity of these blocks to extract the appropriate regions [66].

g) Q-images can also be used to improve edge detection, based on establishing correspondences between edges in the Q-image and edges in the original image [64]. On the use of Q-images as aids in image smoothing see [71].

3. Plans

This section summarizes the planned Maryland/Westinghouse efforts on the next phase of the project, under the title "Understanding features, objects, and backgrounds" (the Westinghouse subcontract will be entitled "Evaluation and real-time implementation of image understanding algorithms"). Section 3.1 dicusses the importance of developing advanced image analysis capabilities for reconnaissance applications. Section 3.2 outlines the proposed approach, and Section 3.3 is a Statement of Work summarizing the principal tasks to be undertaken.

3.1 The problem

The proposed research seeks significant improvements in the processing of sensor images that are involved in both reconnaissance and weapon delivery. Military relevance in these areas is obvious; however, in recent months the demand for progress in the area of weapon delivery has become most urgent. The reason is that several emerging military programs are now predicated on the near-term availability of semi-autonomous or autonomous target acquisition and recognition capability. Examples are the Air Force LANTIRN program and the application of fire-and-forget performance to Army missiles and large caliber projectiles. The decision by the services to place this degree of reliance on image recognition appears to weigh favorably the major improvements in mission performance which might be realized with its use against its present admittedly developmental status.

The performance of present image recognition algorithms, which is to some extent a direct result of earlier work on this Maryland/Westinghouse program, is probably adequate for scenarios which are limited in range and scene content. In more demanding situations it will be lacking. But for any situation improved recognition performance will translate directly into the increased probability of mission success, and where men and equipment are involved, of increased chances for survivability.

How does the target recognition capability that is needed for weapon delivery relate to the more complex evaluation of

reconnaissance images? It appears that the recognition algorithms are a subset of the reconnaissance set. Target extraction is a key element in reconnaissance, but so is the extraction of information which is only indirectly related to targets. As the problems shift from tactical to strategic in nature, their subtlety increases further. Present algorithms are satisfactory for only the simplest of tactical problems. Improvements in performance for any application will require increasingly complex algorithms that make use of all relevant image information. This is the challenge to the algorithm designers. It is an exercise in pure research in image understanding, but with the prospect that positive results will be applied to real problems with very little delay.

Following the initiation and feasibility testing of an algorithm concept, extensive statistical testing is desired, on realistic data bases, in order to establish performance measures. In view of the complexity of the algorithms which are currently under evaluation, the statistical test programs require special processing considerations in order to minimize execution times and computational cost.

In addition to the considerations noted above, the weapon delivery scenario brings with it special demands, including the requirement for real-time performance with equipment having severe limitations in size, weight, power, and cost. The algorithm designer must be aware of, and responsive to, the feasibility of the implementation of his designs in real-time hardware.

3.2 The approach

A. Maryland

Maryland's approach to image understanding and analysis emphasizes highly parallel, cooperating processes which are especially suitable for real-time implementation, particularly a few years from now when parallel cellular hardware becomes readily available, so that it becomes possible to assign a processor to each image pixel. Since such processes make use of very little knowledge at the pixel level, they are subject to errors, which would normally imply the need for backtracking at later stages of the analysis; this would be both difficult and time consuming. To avoid this problem, the initial individual decisions are made fuzzily or probabilistically, and are then checked for consistency with other decisions by an iterative "relaxation" process. This strategy of deferred commitment and use of convergent evidence is designed to minimize the backtracking problem.

Another way in which convergent evidence can be employed at the early stages of image analysis is through the joint use of operators of several types, possibly having a range of sizes. For example, gray level clustering (i.e., thresholding) and edge detection are used jointly in the SUPERSLICE and SUPERLINK algorithms. As another example, spot detectors of several sizes can be used to detect bloblike objects in an image, and local thresholds can then be selected, based on the detector responses, to extract the objects. This last example illustrates

how simple types of size and shape information about the objects that it is desired to extract can be used to influence the extraction process so as to favor their extraction.

Texture analysis too provides some good possibilities for the use of cooperative, parallel computation. Conventional texture features are simple gray level or local property statistics computed over small windows of an image. A potentially more powerful approach to understanding texture is to decompose the given texture into "primitive elements", and measure properties of these primitives, as proposed by Maleson et al. (As a compromise, one can measure gray level or local property statistics at selected points which are expected to be in given positions relative to the primitives, e.g. on or near their borders; this is the "generalized cooccurrence" approach of Davis et al.) Parallel methods of texture primitive extraction, by clustering pairs of antiparallel edges, yield excellent sets of primitives. Cooperative methods can also be used to increase the reliability of texture features measured over small image windows; this makes it possible to use smaller windows and thus reduce the occurrence of mixed windows in an image. These approaches are being extended to multiple resolutions and multiple window sizes.

Edge clustering is also an economical approach to the detection of cultural features such as roads and buildings in

imagery. An approach is under investigation in which edge information is iteratively enhanced, by a relaxation-like process, and edge pixels are then linked into edge segments. These segments are then clustered, in a Hough-like space, on the basis of collinearity and antiparallelness, yielding pieces of linear features. Finally, a relaxation approach is used to probabilistically label these pieces as to feature type, and iteratively adjust the probabilities so as to reconcile the labels of related pieces, thus obtaining a consistent global labeling.

The relaxation approach is also being used for shape recognition and matching. The border of a given shape, or collection of touching shapes, is ambiguously segmented, and the segments are probabilistically labelled. The probabilities are then adjusted based on their compatibilities with those of related segments. This yields a relatively unambiguous labeling from which it is easy to find segment sequences that correspond to shapes of the desired types. This approach is being extended to handle hierarchical shape descriptions. Cooperative techniques can also be used at a lower level to produce the original shape segmentations.

Compact hierarchical representations for images and regions, based on quadtree data structures, have been extensively studied on the current project. It is planned to extend this work from exact to approximate representation; a block is subdivided

if its contents are sufficiently nonuniform. (This is, of course, the well-known approach to image segmentation by recursive splitting.) Algorithms will be developed for efficiently computing properties of images directly from this representation, and for converting between this and other representations. These will generalize the algorithms developed for the case of exact representation on the current project, and will make the work applicable to a wide class of images.

The principal goal of the project will be the study of algorithms that can be used for object detection on tactical imagery, and that are potentially implementable in real time. There will be close collaboration with the U.S. Army Night Vision and Electro-Optics Laboratory, as monitoring agency, as well as with Westinghouse, in selecting appropriate problems from this domain.

Many of the algorithms developed on this project will also be applicable to the planned DARPA/DMA Image Understanding testbed. It is proposed to contribute a collection of such algorithms for the testbed in the form of an interactive program that will allow the user to define his problem, prompt him to provide traning samples (e.g., of objects and background, of textures, etc.) for analysis, recommend applicable techniques, apply them to the image, and display the results for evaluation. This will provide an extensible capability for interactive selection and evaluation of segmentation and texture analysis techniques as

modular front ends to an image analysis process. This capability should be useful in connection with most of the imagery that other contributors to the testbed will analyze, or that users of the testbed may want to analyze.

B. Westinghouse

During the current DARPA program Westinghouse has explored the feasibility of the LSI implementation of a series of algorithms developed by Maryland for higher level image processing, particularly in the area of relaxation processes. Concurrent with this effort a second potential task of algorithm evaluation has emerged. This is because the Maryland algorithms are sufficiently complex as to require many minutes to process a single sample window on a general-purpose computer. Since a statistical test, as developed by NVEOL for example, may include 400 to 1000 image samples, detailed consideration must be given to the test approach. A solution to this problem has been proposed at Westinghouse, using fully programmable array processors as a means to achieve high throughput with great flexibility. It offers the additional advantage of a means for LSI implementation with little or no reprogramming, since Westinghouse is developing a series of LSI chips (Universal Arrays) for implementation of array processors.

The proposed program of algorithm evaluation and implementation has emerged in the form indicated by Figure 13. This diagram portrays the evolution of a miniaturized image processor from the initial concept to hardware. The steps performed

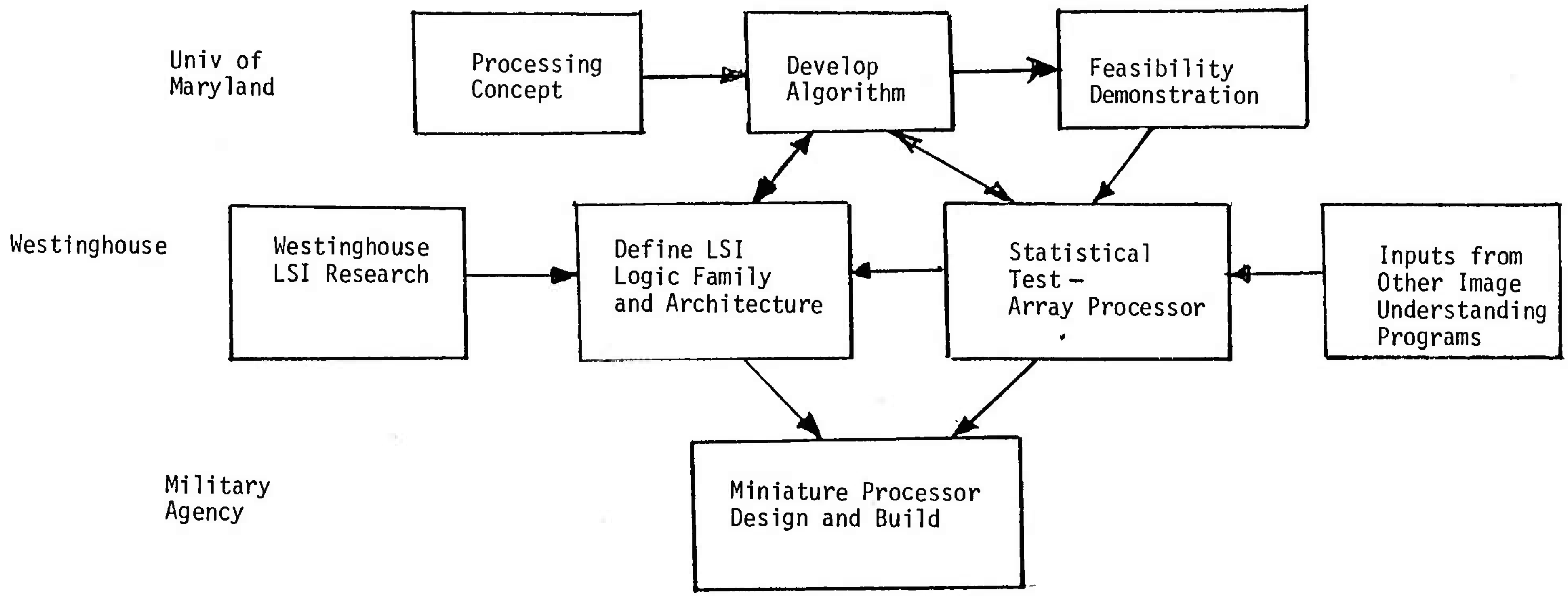


Figure 13. EVOLUTION FROM PROCESSING CONCEPT TO MINIATURIZED HARDWARE

by the University of Maryland are shown across the top of the figure. Following algorithm development, Maryland will perform feasibility testing with a limited data base, using a general-purpose computer for simulation. With the test results in hand, as well as the algorithm statement itself, Westinghouse will develop the necessary programming to perform a statistical test of the algorithm with a data base selected or approved by NVEOL, and involving tactical imagery. Westinghouse may also assist in data base compilation if necessary, using its laboratories for conversion of video data into digital format.

In addition to examining algorithms generated by Maryland, Westinghouse proposes to examine algorithms described by other university participants in the Image Understanding Program. Algorithms of interest will be statistically tested on the same data bases. Test results will be provided to all program participants.

The algorithm design, together with the statistical test results, will form the basis for a design feasibility study for implementation of miniaturized hardware. This effort will be aided by company-sponsored investigations of the available LSI families, and their associated system architectures. The results will be made available to various military agencies, such as NVEOL, for further design and construction effort.

3.3 Statement of Work

A. Maryland

The proposed project will emphasize the development of image analysis algorithms suitable for real-time implementation. Specific areas of investigation will include:

a. Segmentation techniques for object extraction that make use of convergent evidence--e.g., gray level clustering in conjunction with edge, spot, or streak detection, at multiple resolutions.

b. Texture analysis techniques for background analysis and terrain classification, based on the extraction and characterization of primitive texture elements, as well as on the use of multiple-resolution interactions to enhance texture property measurements.

c. Methods of extracting macroscopic image features such as roads and buildings by clustering of edges into feature segments, and using relaxation-like techniques to find consistent labellings of these segments.

d. Shape recognition techniques based on ambiguous segmentation and on the use of relaxation methods to find consistent sets of segments. Relaxation will also be applied to pattern detection problems, e.g., to detecting arrays of jointly occurring small objects which satisfy given constraints on their relative positions.

e. The use of compact representations such as quadtrees for image approximation and compression, as well as for

the exact representation of regions so as to provide efficient methods of handling region databases.

f. In conjunction with NVEOL and Westinghouse, a set of practical analysis tasks will be selected, together with appropriate databases. The "Alabama" data base, consisting of FLIR images of tactical targets at low and high resolution, will be used initially, since test results with it have been obtained for several existing algorithms. The "Ft. Polk" and "A.P. Hill" data bases increase the variety of tactical targets that can be observed, as well as the background conditions. Target motion and obscuration are also present. Additional databases available at Westinghouse can further increase the variety of sensor types, target characteristics, and environmental conditions.

It is desired by NVEOL to acquire additional databases which provide contextual information to assist in target classification, including the occurrence of military target groups or clusters. Use of such contextual information is an important aspect of higher level image understanding.

Algorithms will be tested on small data sets, and promising algorithms will be recommended to Westinghouse for further testing and for possible hardware design.

g. It is also planned to provide a collection of algorithms, particularly in areas (a-c), for use in the DARPA/DMA testbed, in the form of an interactive package. As presently envisioned, the package will provide users with a menu of basic segmentation, texture analysis, and feature extraction techniques. Users will not need to be familiar with these techniques; they will be prompted to provide information on the basis of which the system will make choices and present results for evaluation. For example, if a user wishes to extract objects from a background, he will be asked to define (via cursor) samples of the objects and background; the system will then select an appropriate segmentation technique, apply it to the image, and request him to critique the results--e.g., to indicate errors (via cursor)--so that the technique can be refined as necessary. It is planned to work closely with SRI, as testbed implementors, so that this package can be closely integrated with the testbed software.

B. Westinghouse

The proposed program will be directed toward the evaluation and implementation of image processing algorithms developed by the University of Maryland or others involved in the DARPA

Image Understanding program. Initial effort will be concerned with the inclusion of relaxation operations in the preprocessor functions. Results will be compared with the Maryland "Superslice" and Westinghouse AUTO-Q algorithms. In addition, close attention will be given to the "primal sketch" operations described by MIT.

Specific tasks will include:

a. Review of Maryland and other IU programs for candidate algorithms.

b. Acquisition and refinement of data bases appropriate to both weapon delivery and reconnaissance scenarios, and determination of candidate scenarios in coordination with NVEOL. Such scenarios include the helicoptor pop-up operation, and target handoff from an aircraft sensor to a missile seeker.

c. Statistical testing of algorithms using appropriate simulation tools, such as array processors. Results to be reported to algorithm designer.

d. Perform design feasibility analyses for hardware implementation of successful algorithms, with consideration of available LSI families. Provide recommendations for applications of successful algorithms to military systems.

e. Deliverable items under the contract will be the test results on candidate algorithms and hardware design information, including resources required for imple-

mentation. Reports will contain comparative evaluations of algorithms. Transportable software will be provided.

Success on the program will be measured by the performance improvements which are statistically demonstrated in terms of target detection and classification rates, and the reduction of false alarms. Such improvements will constitute advances in the state of the art, and will thus assure that hardware implementation will occur. This sequence of events was demonstrated during the first phase of this program, with the "Superslice" algorithm.

4. Publications

This section lists status reports, technical reports, and papers published on the current phase of the project, under the following headings:

A. Semiannual reports (as well as the Final Report on the previous phase of the project), project status reports, and quarterly reports on the Westinghouse subcontract

B. Technical reports

C. Papers

For convenience, a brief outline of the individual research areas on the project is given in Sections 4.1-2, with references to the reports that relate to each area.

4.1 Object detection

	Topic	Report Nos.
a. Preprocessing	Noise cleaning techniques	29,29,34,71,72
	"Probability transforms"	38
	Gaussian convolution	63
b. Edge detection	Color edge detection	18
	Straight edge enhancement	22
	Step-fitting edge detection	33
	Pyramid edge enhancement	64
	Edge maxima	67
c. Corner, line, and strip detection	Strip detection	27
	Antiparallel linking	57
	Collinearity linking	67
	Gray-level corner detection	69
	Clustering of collinear segments	70
d. Pixel classification	ISODATA thresholding	35
	Relaxation thresholding	55
	Relaxation "busyness" clustering	65
	Pyramid thresholding	68
e. Segmentation	SUPERSLICE	19
	SUPERLINK	24
	Blob detection by relaxation	50
	Pyramid blob and streak detection	52,60
	Pyramid "SUPERSLICE"	66

4.2 Tools for image understanding

	Topic	Report Nos.
a. Image models	Mosaic model fitting	32,47
b. Texture analysis	Generalized cooccurrence	30
	Primitive extraction	40
	Feature smoothing	56
c. Shape analysis	Segmentation by relaxation	39,48
	Segmentation by global features	59
d. Region representation	Quadtrees and pyramids	28,31,36,37, 41-46,49,51, 54,58,62
	Medial axes	61,73
e. Matching	Point patterns	21,23,26
	Relational structures	17,25
f. Software	Control structures	16
	Utility packages	53,55

A. Project reports

A1. Final Report on first phase

1. Algorithms and Hardware Technology for Image Recognition, Final Report, March 31, 1978.

A2. Semiannual reports and project status reports: Image Understanding Using Overlays

2. Semiannual report, 1 April-30 September 1978.

3. Semiannual report, 1 October 1978-31 March 1979.

4. Semiannual report, 1 April-30 September 1979.

5. Project status report, 1 April-30 September 1978, in Proceedings, Image Understanding Workshop, November 1978, 20-27.

6. Project status report, 1 October-31 March 1979, in Proceedings, Image Understanding Workshop, April 1979, 14-24.

7. Project status report, 1 April-30 September 1979, in Proceedings, Image Understanding Workshop, November 1979, 166-175.

8. Project status report, 1 October 1979-31 March 1980, in Proceedings, Image Understanding Workshop, April 1980, 1-12.

A3. Quarterly reports on Westinghouse subcontract: Architecture for Higher Level Digital Image Processing

9. First quarterly report, July 30, 1978.

10. Second quarterly report, October 30, 1978.

11. Third quarterly report, January 30, 1979.

12. Fourth quarterly report, April 30, 1979.

13. Fifth quarterly report, July 31, 1979.

14. Sixth quarterly report, October 31, 1979.

15. Seventh quarterly report, January 31, 1980.

B. Technical reports

16. Martin Herman, "A System for Control Structure Implementation for Image Understanding." TR-646, March 1978.

17. Les Kitchen, "Discrete Relaxation for Matching Relational Structures." TR-665, June 1978.

18. P. V. Sankar, "Color Edge Detection: A Comparative Study." TR-666, June 1978.

19. D. L. Milgram, "Region Extraction Using Convergent Evidence." TR-674, June 1878.

20. Judith P. Davenport, "A Comparison of Noise Cleaning Techniques." TR-689, September 1978.

21. Daryl J. Kahl, Azriel Rosenfeld, and Alan Danker, "Some Experiments in Point Pattern Matching." TR-690, September 1978.

22. Shmuel Peleg and Azriel Rosenfeld, "Straight Edge Enhancement and Mapping." TR-694, September 1978.

23. Sanjay Ranade and Azriel Rosenfeld, "Point Pattern Matching by Relaxation." TR-702, October 1978.

24. David L. Milgram, "Edge Point Linking Using Convergent Evidence." TR-704, October 1978.

25. Les Kitchen, "Relaxation Applied To Matching Quantitative Relational Structures." TR-707, October 1978.

26. Daryl J. Kahl, "Sketch Matching." TR-716, November 1978.

27. Alan Danker and Azriel Rosenfeld, "Strip Detection Using Relaxation." TR-725, January 1979.

28. Charles R. Dyer, Azriel Rosenfeld, and Hanan Samet, "Region Representation: Boundary Codes from Quadtrees." TR-732, February 1979.

29. Ann Scher, Flavio R. D. Velasco, and Azriel Rosenfeld, "Some New Image Smoothing Techniques." TR-733, February 1979.

30. Charles R. Dyer, Tsai-Hong Hong, and Azriel Rosenfeld, "Texture Classification Using Gray Level Cooccurrence Based on Edge Maxima." TR-738, March 1979.

31. Hanan Samet, "Region Representation: Quadtrees from Boundary Codes." TR-741, March 1979.

32. Tsvi Dubitzki, Narendra Ahuja, and Azriel Rosenfeld, "Predicted Properties of Mosaic Images." TR-746, March 1979.

33. Azriel Rosenfeld, "The Simplest 'Hueckel' Edge Detector is a Roberts Operator." TR-747, March 1979.

34. Judith P. Davenport and Azriel Rosenfeld, "A Comparison of Noise Cleaning Techniques for Color Images." TR-748, April 1979.

35. Flavio R. D. Velasco, "Thresholding Using the Isodata Clustering Algorithm." TR-751, March 1979.

36. Hanan Samet, "Computing Perimeters of Images Represented by Quadtrees." TR-755, April 1979.

37. Hanan Samet, "Connected Component Labeling Using Quadtrees." TR-756, April 1979.

38. Ann Scher and Azriel Rosenfeld, "'Probability Transforms' of Digital Pictures." TR-758, April 1979.

39. Wallace S. Rutkkowski, Shmuel Peleg, and Azriel Rosenfeld, "Shape Segmentation Using Relaxation." TR-762, May 1979.

40. Tsai-Hong Hong, Charles R. Dyer, and Azriel Rosenfeld. "Texture Primitive Extraction Using an Edge-Based Approach." TR-763, May 1979.

41 Hanan Samet, "Region Representation: Raster-to-Quadtree Conversion." TR-766, May 1979.

42. Hanan Samet, "Region Representation: Quadtrees from Binary Arrays." TR-767, May 1979.

43. Hanan Samet, "Region Representation: Quadtree-to-Raster Conversion." TR-768, June 1979.

44. Charles R. Dyer, "Computing the Euler Number of an Image from Its Quadtree." TR-769, May 1979.

45. Michael Shneier, "Linear Time Calculations of Geometric Properties Using Quadtrees." TR-770, May 1979.

46. Hanan Samet, "A Distance Transform for Images Represented by Quadtrees." TR-780, July 1979.

47. Narendra Ahuja and Azriel Rosenfeld, "Fitting Mosaic Models to Textures." TR-789, July 1979.

48. Wallace S. Rutkowski, "Shape Segmentation Using Relaxation, II." TR-793, July 1979.

49. Michael Shneier, "A Path-Length Distance Transform for Quadtrees." TR-794, July 1979.

50. Alan Danker, "Blob Detection by Relaxation." TR-795, July 1979.

51. Hanan Samet, "A Quadtree Medial Axis Transform." TR-803, August 1979.

52. Michael Shneier, "Using Pyramids to Define Local Thresholds for Blob Detection." TR-808, September 1979.

53. Robert L. Kirby, Russ Smith, Philip A. Dondes, Sanjay Ranade, Les Kitchen, and Fred Blonder, "Interfaces, Subroutines, and Programs for the Grinnell GMR-27 Display Processor on a PDP-11/45 with the UNIX Operating System." TR-810, October 1979.

54. Peter J. Burt, "Tree and Pyramid Structures for Coding Hexagonally Sampled Binary Images." TR-814, October 1979.

55. Russell C. Smith, "A General-Purpose Software Package for Array Relaxation." TR-839, December 1979.

56. Tsai-Hong Hong, Angela Y. Wu, and Azriel Rosenfeld, "Feature Value Smoothing as an Aid in Texture Analysis." TR-844, December 1979.

57. Ann Scher, Michael Shneier, and Azriel Rosenfeld, "A Method for Finding Pairs of Anti-parallel Straight Lines." TR-845, December 1979.

58. Sanjay Ranade, Azriel Rosenfeld, and Hanan Samet, "Shape Approximation Using Quadtrees." TR-847, December 1979.

59. W. S. Rutkowski, "Shape Segmentation Using Arc/Chord Properties." TR-849, December 1979.

60. Michael Shneier, "Extracting Linear Features from Images Using Pyramids." TR-855, January 1980.

61. Shmuel Peleg and Azriel Rosenfeld, "A Min-Max Medial Axis Transformation." TR-856, January 1980.

62. Hanan Samet, "Neighbor Finding Techniques for Images Represented by Quadtrees." TR-857, January 1980.

63. Peter J. Burt, "Fast, Hierarchical Correlations with Gaussian-Like Kernels." TR-860, January 1980.

64. Sanjay Ranade, "Use of Quadtrees for Edge Enhancement." TR-862, February 1980.

65. Philip A. Dondes and Azriel Rosenfeld, "Pixel Classification Based on Gray Level and Local 'Busyness.'" TR-874, March 1980.

66. Sanjay Ranade, Azriel Rosenfeld, and Judith M. S. Prewitt, "Use of Quadtrees for Image Segmentation." TR-878, February 1980.

67. Les Kitchen, Alan Broder, and Azriel Rosenfeld, "Two Notes on Digital Edges and Lines." TR-885, March 1980.

68. Angela Y. Wu, Tsai-Hong Hong, and Azriel Rosenfeld, "Threshold Selection Using Quadtrees." TR-886, March 1980.

69. Les Kitchen and Azriel Rosenfeld, "Gray-level Corner Detection." TR-887, April 1980.

70. Ann Scher, Michael Shneier, and Azriel Rosenfeld, "Clustering of Collinear Line Segments." TR-888, April 1980.

71. Sanjay Ranade and Michael Shneier, "Using Quadtrees to Smooth Images." TR-894, April 1980.

72. Shmuel Peleg, "Elimination of Seams from Photomosaics." TR-895, April 1980.

73. Shyuan Wang, Angela Y. Wu, and Azriel Rosenfeld, "Image Approximation from Grayscale 'Medial Axes.'" TR-900, May 1980.

C. Papers

C1. DARPA Image Understanding Workshops

74. D. L. Milgram, Edge point linking using convergent evidence (November 1978, 85-91).

75. A. Rosenfeld, Some experiments in matching using relaxation (November 1978, 110-114).

76. T. J. Willett, Hardware implementation of image processing using overlays: relaxation (November 1978, 175-181).

77. A. Rosenfeld, A. Danker, and C. R. Dyer, Blob extraction by relaxation (April 1979, 61-65).

78. T. J. Willett, C. W. Brooks, and G. E. Tisdale, Relaxation, systolic arrays, and universal arrays (April 1979, 164-170).

79. T. J. Willett, A. R. Helland, and G. E. Tisdale, Higher level algorithms: evaluation and implementation (November 1979, 15-24).

80. C. Rieger, ZMOB: A mob of 256 cooperative Z80A-based microcomputers (November 1979, 25-30).

81. M. Shneier, Using pyramids to define local thresholds for blob detection (November 1979, 31-35).

82. H. Samet and A. Rosenfeld, Quadtree structures for region processing (November 1979, 36-41).

83. A. Rosenfeld, Cooperative computation in texture analysis (November 1979, 52-56).

84. A. Rosenfeld, Levels of representation in cultural feature extraction (November 1979, 112-127).

85. M. Tavakoli, Toward the recognition of cultural features (April 1980, 33-57).

86. A Rosenfeld, Some uses of pyramids in image processing and segmentation (April 1980, 112-120).

87. A. R. Helland, Convergence properties of two label relaxations (April 1980, 176-181).

C2. Journal and conference papers (accepted or published)

88. L. Kitchen and A. Rosenfeld, Discrete relaxation for matching relational structures, IEEETSMC-9, 1979, 869-874.

89. D. L. Milgram, Region extraction using convergent evidence, CGIP 11, 1972, 1-12.

90. D. J. Kahl, A. Rosenfeld, and A. Danker, Some experiments in point pattern matching, IEEETSMC-10, 1980, 105-116.

91. S. Ranade and A. Rosenfeld, Point pattern matching by relaxation, Pat. Recog. 12, 1980, in press.

92. L. Kitchen, Relaxation applied to matching quantitative relational structures, IEEETSMC-10, 1980, 96-101.

93. A. Danker and A. Rosenfeld, Strip detection using relaxation, Pat. Recog. 12, 1980,97-100.

94. C. R. Dyer, A. Rosenfeld, and H. Samet, Region representation: boundary codes from quadtrees, CACM 23, 1980, 171-179.

95. A. Scher, F. R. D. Velasco, and A. Rosenfeld, Some new image smoothing techniques, IEEETSMC-10, 1980, in press.

96. C. R. Dyer, T-H. Hong, and A. Rosenfeld, Texture classification using gray level cooccurrence based on edge maxima, IEEETSMC-10, 1980, in press.

97. H. Samet, Region representation: Quadtrees from boundary codes, CACM 23, 1980, 163-170.

98. A. Rosenfeld, The MAX Roberts operator is a Hueckel-type edge detector, IEEETPAMI-2, 1980, in press.

99. F. R. D. Velasco, Thresholding using the ISODATA clustering algorithm, IEEETSMC-10, 1980, in press.

100. H. Samet, Connected component labeling using quadtrees, JACM, in press.

101. A. Scher and A. Rosenfeld, "Probability transforms" of digital pictures, Pat. Recog. 12, 1980, in press.

102. W. S. Rutkowski, S. Peleg, and A. Rosenfeld, Shape segmentation using relaxation, IEEETPAMI-2, 1980, in press.

103. T. H. Hong, C. R. Dyer, and A. Rosenfeld, Texture primitive extraction using an edge-based approach, IEEETSMC-10, 1980, in press.

104. H. Samet, Region representation: raster-to-quatree conversion, IEEETPAMI-2, 1980, in press.

105. H. Samet, Region representation: quadtrees from binary arrays, CGIP, in press.

106. C. R. Dyer, Computing the Euler number of an image from its quadtree, CGIP, in press.

107. N. Ahuja and A. Rosenfeld, Fitting mosaic models to textures, in R. M. Haralick, ed., Image Texture Analysis, Plenum Press, NY, in press.

108. A. Danker and A. Rosenfeld, Blob extraction by relaxation, IEEETPAMI-2, 1980, in press.

109. T. H. Hong, A. Y. Wu, and A. Rosenfeld, Feature value smoothing as an aid in texture analysis, IEEETSMC-10, 1980, in press.

110. S. Peleg and A. Rosenfeld, A min-max medial axis transformation, IEEETPAMI-2, 1980, in press.

111. H. Samet, Neighbor finding techniques for images represented by quadtrees, CGIP, in press.

112. S. Peleg, Elimination of seams from photomosaics, CGIP, in press.

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Appendix. Summaries of Quarterly Reports on Westinghouse Subcontract: "Architecture for Higher Level Digital Image Processing"

1. First Quarterly Report, July 30, 1978.

The report begins with a review of desired system design goals. This is followed by a description of available microprocessor hardware, a review of the LISP approach to the manipulation of list structures, and a preliminary discussion of the processing required to implement relaxation methods of object classification. The report concludes with a description of specific bit-slice processors.

2. Second Quarterly Report, October 30, 1978.

This report begins with a continuation of a description of bit slice microprocessors with the emphasis on control units this time, and an examination of commercially available units. Several more Maryland algorithms, namely non-linear probabilistic relaxation, connected components, and Superlink are described. Hardware implementations for non-linear probablistic relaxation and connected components are described in the next section. The final section shows some tentative conclusions, in light of the above continuing analysis, regarding an appropriate architecture for image processing both for the image processing module and the array of modules.

3. Third Quarterly Report, January 30, 1979.

This report begins with a description of the computations for performing relaxation at the pixel level in order to divide an image into dark and light regions. The computations are restructured to conform to a matrix multiplied by a vector, multiplied by a scalar. A "Systolic"* array of processors is applied to this computational structure and the results described. The individual processors take a particular form of the Westinghouse Universal Array currently being developed for 20 mega-operations/sec. signal processors. One personalization of the Universal Array in the systolic array architecture is a self-contained, 4x4 multiply chip with a 12-nanosecond 8-bit product. The computations are also restructured to delete frame storage and permit computational speeds approaching real time, while still maintaining a small volume.

4. Fourth Quarterly Report, April 30, 1979.

This report considers hardware implementation of Relaxation Processes using cellular automata architecture with Universal Arrays as the central solid state module. The work examines the edge/no edge and light/dark algorithms. In particular, an effort has been directed to the development of a cellular array

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*Kung, H. T., and Leiserson, C. E., Systolic Arrays for VLSI, Dept. of Computer Science, Carnegie-Mellon University, Dec., 1978. "Systolic Array" is a term used by H. T. Kung to describe a network of processors which rhythmically compute and pass data through the system.

module which shows promise. It can be operated at speeds comparable to frame rates, and in part can be composed of a Universal Array multiplier and a Universal Array multiplexer.

5. Fifth Quarterly Report, July 31, 1979.

This report deals primarily with the definition of digital architecture for implementing the image processing algorithms developed at the University of Maryland. A need has also emerged to provide support to the University of Maryland in the statistical testing of complex algorithms. This had led to an investigation of programmability of these algorithms on a fully programmable array processor (PAP) developed at Westinghouse.

6. Sixth Quarterly Report, October 31, 1979.

This report covers results of special analysis performed as part of the recent work to support the University of Maryland in the statistical testing of complex algorithms. The planned steps in this support program are:

Selection of processing algorithms for evaluation.

Analysis and adaptation of algorithms for execution on the Programmable Array Processor (PAP).

Evaluation of algorithms on a PDP-VAX GP computer.

Throughput analysis; PAP vs. VAX.

Processing of a set of imagery.

Results are reported at regular intervals as appropriate.

This report analyzes the segmentation properties of gray level relaxation applied to the two-label case. The results produce threshold, speed and stability criteria to facilitate subsequent processing. Most of these results are experimentally verified in a report by Azriel Rosenfeld and Russell C. Smith. Evaluation and verification is in progress at Westinghouse using comparable imagery and test patterns. The current status of the computer program modeling and test results will be covered in a separate report to be completed shortly. Efforts underway and planned for the immediate future include evaluation of image samples on the VAX, throughput analysis for the PAP, and relaxation processing for multiple label cases. The analysis and subsequent testing is intended to apply to monochrome TV or FLIR imagery (hence, one-dimensional data) and usually only one object polarity (two labels) with extension to both object polarities in the same imagery (three labels).

7. Seventh Quarterly Report, January 31, 1980.

This report contains results of relaxation processing performed by Westinghouse to demonstrate speed, threshold, and convergence properties using test patterns and FLIR imagery. This evaluation was performed on the PDP-VAX GP computer in preparation for the processing of a set of imagery on the Westinghouse Programmable Array Processor (PAP).

REPORT DOCUMENTATION PAGE

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)
This project is concerned with the study of advanced techniques for the analysis of reconnaissance imagery. It is being conducted under Contract DAAG-53-76C-0138 (DARPA Order 3206), monitored by the U.S. Army Night Vision Laboratory, Ft. Belvoir, VA (Dr. George Jones). The Westinghouse Systems Development Division, as a subcontractor, is investigating implementation of the techniques being developed by Maryland; the subcontract is entitled "Architecture for higher level digital image processing".